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# A Comparative Study of Machine Learning Models for Short-Term Load Forecasting

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***Abstract***
*Short-Term Load Forecasting (STLF) was a critical task in power system operations, enabling efficient energy management and planning. This study presented a comparative analysis of five machine learning models namely XGBoost, Random Forest, Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), and LightGBM using real-world electricity demand data collected over a four-month period. Two modeling approaches were explored: one using only time-based features (hour, day of the week, month), and another incorporating historical lag features (lag_1, lag_2, lag_3) to capture temporal patterns. The results showed that MLP with lag features achieved the best performance (RMSE: 57.63, MAE: 34.54, MAPE: 0.22), highlighting its ability to model nonlinear and sequential dependencies. In contrast, SVR and LightGBM experienced performance degradation when lag features were added, suggesting sensitivity to feature dimensionality and data volume. These findings emphasized the importance of model-feature alignment and temporal context in improving forecasting accuracy. Future work could explore the integration of external variables such as weather and holidays, as well as the application of advanced deep learning architectures like LSTM or hybrid models to further enhance robustness and generalizability.*

***Keywords*** *: Short-Term Load Forecasting, Machine Learning Models, Lag Features, Electricity Demand Prediction, Model Evaluation*

## 1 Introduction

The increasing demand for electricity, driven by population growth, urbanization, and the expansion of smart technologies, has made accurate short-term load forecasting (STLF) a vital component in modern power systems. STLF enables utility providers to optimize energy distribution, reduce operational costs, and maintain grid stability [1], [2]. Traditional statistical methods such as ARIMA and exponential smoothing have been widely used for load prediction, but they often struggle to capture the nonlinear and dynamic nature of electricity consumption patterns [3].

In contrast, machine learning (ML) techniques have gained prominence due to their ability to model complex relationships and adapt to changing data trends [4], [5]. These models offer improved forecasting accuracy and flexibility, making them suitable for real-time energy management applications [6]. Various ML models have been applied to STLF, including tree-based methods like Random Forest and XGBoost, neural networks such as Multi-Layer Perceptron (MLP), and kernel-based approaches like Support Vector Regression (SVR) [7], [8]. Deep learning models, such as

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Long Short-Term Memory (LSTM) and Time-Augmented Recurrent Neural Networks (TARNN), have also demonstrated strong performance in capturing temporal dependencies [1], [3], [4].

However, the effectiveness of these models is highly dependent on the quality and structure of input features. Feature engineering, particularly the inclusion of time-based (e.g., hour, day, month) and historical (lag) features, plays a crucial role in enhancing model performance [9], [10]. Several studies have shown that lag features significantly improve forecasting accuracy by capturing temporal trends and autocorrelation in electricity demand [9], [10]. Despite these advancements, many existing studies focus on a single model or a narrow comparison between models, often under inconsistent data or feature configurations [10].

This study addresses these gaps by conducting a comprehensive comparative analysis of five machine learning models (XGBoost, Random Forest, MLP, SVR, and LightGBM) using real-world electricity demand data. Two feature configurations are evaluated: one using only time-based features and another incorporating lag features. The models are assessed using standard performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). This dual-configuration approach provides deeper insights into how different models respond to feature variations and which combinations yield the most accurate forecasts. By systematically evaluating the impact of lag features across multiple ML models, this research aims to identify the most effective model-feature combination and offer practical guidance for future forecasting system development.

## 2 Literature Review

Short-Term Load Forecasting (STLF) has long been a critical area of research in power system operations, driven by the need for efficient energy management, cost reduction, and grid stability. Traditional statistical methods such as ARIMA and exponential smoothing have been widely used in early forecasting models. However, these methods often fall short in capturing the nonlinear and dynamic nature of electricity consumption patterns, especially in modern, data-rich environments [3].

In recent years, machine learning (ML) techniques have gained prominence due to their ability to model complex relationships and adapt to evolving data trends. Studies have demonstrated the effectiveness of various ML models, including tree-based methods like Random Forest and XGBoost, neural networks such as Multi-Layer Perceptron (MLP), and kernel-based approaches like Support Vector Regression (SVR) [4], [5], [7], [8]. These models offer improved accuracy and flexibility, making them suitable for real-time applications in energy forecasting.

Moreover, deep learning models such as Long Short-Term Memory (LSTM) and Time-Augmented Recurrent Neural Networks (TARNN) have shown strong performance in capturing temporal dependencies in load data [1], [3], [4]. These models are particularly effective in scenarios where sequential patterns and long-term dependencies play a significant role. A key factor influencing the performance of ML models in STLF is feature engineering. The inclusion of time-based features (e.g., hour, day of the week, month) and historical lag features (e.g., lag_1, lag_2, lag_3) has been shown to significantly enhance forecasting accuracy [9], [10]. Lag features, in particular, help models capture short-term trends and autocorrelation in electricity demand, which are crucial for accurate predictions. Despite these advancements, many existing studies focus on a single model or a limited comparison under varying data conditions, leading to inconsistent conclusions.

There is a growing need for comprehensive comparative analyses that evaluate multiple models under standardized conditions to identify the most effective approaches for STLF.

This study addresses this gap by comparing five widely used ML models (XGBoost, Random Forest, MLP, SVR, and LightGBM) under two feature configurations that are using only time-based features and another incorporating lag features. This dual-configuration approach provides deeper insights into the role of temporal context in improving forecasting performance and offers practical guidance for future model development.

Recent studies demonstrated the effectiveness of each of the five machine learning models evaluated in this study. XGBoost was widely used in STLF due to its high accuracy and computational efficiency. For example, [11] implemented a hybrid model combining XGBoost with LSTM for electricity demand forecasting and reported superior performance compared to standalone models. [12] compared XGBoost with Random Forest and linear regression for forecasting Turkey's electricity consumption and found XGBoost to be the most accurate. Random Forest was also extensively applied in STLF. [13] conducted a comprehensive study on Random Forest for STLF and found that it consistently outperformed both statistical and other ML models across multiple datasets. Additional studies showed that Random Forest performed well in hybrid configurations and remained robust to overfitting. MLP (Multi-Layer Perceptron) showed strong performance in various forecasting tasks. A 2025 study by Liu et al. [14] proposed a deep learning framework for STLF using attention mechanisms and demonstrated that MLP-based models achieved competitive accuracy on real-world smart grid datasets. Another study by [15] applied MLP in forecasting power consumption in AI data centers and confirmed its ability to model nonlinear and dynamic load patterns. SVR (Support Vector Regression) continued to be used in STLF research, particularly for its robustness in small datasets and its ability to handle nonlinear regression problems. [16] proposed an SVR model optimized with a whale optimization algorithm and demonstrated improved accuracy compared to other models. [17] also explored the influence of data normalization on SVR performance in STLF and highlighted its sensitivity to preprocessing techniques. LightGBM, although relatively newer, gained popularity for its speed and scalability. [18] integrated LightGBM into a hybrid forecasting framework and achieved high accuracy in multi-frequency sequence prediction. [19] investigated the influence of hyperparameters on LightGBM performance in load forecasting and emphasized the importance of tuning for optimal results. [20] applied optimized LightGBM in a transfer learning-based hybrid model for smart grid forecasting and reported competitive results. These studies supported the claim that the five models selected in this research were among the most widely used and relevant for short-term load forecasting.

In addition to model selection, the accuracy of predictions in STLF is significantly influenced by the quality and resolution of the input data. High-resolution data, such as hourly or 15-minute intervals that enables models to capture finer fluctuations and short-term seasonal patterns in electricity demand. However, such data also requires greater computational resources and more sophisticated preprocessing techniques to mitigate issues like overfitting and noise [6].

Several studies also emphasize the importance of comprehensive model evaluation using multiple performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Relying on a single metric often fails to provide a complete picture of model performance, especially when data distributions are uneven or contain outliers. As a result, multi-metric evaluation has become a standard practice in STLF research to ensure a more reliable assessment of forecasting models [1], [2], [4], [5].

Finally, recent trends in STLF research show a growing interest in hybrid and ensemble models, which combine the strengths of multiple algorithms to enhance prediction accuracy and robustness. For instance, integrating LSTM with XGBoost or combining statistical models with machine learning techniques has proven effective in overcoming the limitations of individual methods. These approaches open new possibilities for developing adaptive and resilient forecasting systems that can better respond to evolving electricity consumption patterns [1], [3], [4].

## 3 Research Methods

This study employs a systematic methodology to evaluate the effectiveness of various machine learning models in short-term load forecasting. The process includes data collection, preprocessing, model training, evaluation, and comparison of results using two feature configurations: Non-STLF and STLF. Each model is assessed using RMSE and MAE metrics to ensure a fair and consistent performance comparison. Research Method Flowchart can be seen in Figure 1.

### 3.1 Data Collection

The dataset comprises 40 entries with four key columns: Delivery Date, From GMT, To GMT, and DFS Required MW. Data was collected from [https://www.neso.energy/data-portal/demand-flexibility-service-test-events]. The data collection process in this study utilized real-world electricity demand data. This dataset was recorded at 30-minute intervals, allowing for a detailed analysis of short-term consumption patterns. The data spans from November 15, 2022, to March 28, 2023, covering various daily and seasonal conditions. This time range ensures a representative sample for developing and evaluating forecasting models. The quality and granularity of the data are crucial, as they form the foundation for accurate and reliable model training.

The collected data reflects fluctuations in electricity usage influenced by temporal factors such as hour of the day, day of the week, and month. It also supports the creation of lag features, which are essential for short-term load forecasting models. Before being used in modeling, the data was chronologically sorted and the date and time were combined into a single datetime format. This preprocessing step ensures that the temporal sequence is preserved, which is vital for time series analysis. With high-resolution and well-structured data, the forecasting models can learn patterns more effectively and deliver better performance.

### 3.2 Data Preprocessing

The data preprocessing stage began with merging the separate date and time columns into a unified datetime format. This step was crucial for enabling time-based analysis and ensuring that the temporal sequence of the data was preserved. By converting the data into datetime format, it became easier to extract relevant time features such as hour, day of the week, and month. This transformation also facilitated chronological sorting, which is essential for time series forecasting. Ensuring the correct order of data points helps maintain the integrity of the temporal relationships within the dataset.

After formatting the datetime values, the dataset was sorted in ascending chronological order. This sorting ensured that the training and testing datasets reflected the natural flow of time, which is vital for accurate forecasting. Any inconsistencies or missing values were addressed during this phase to maintain data quality. The cleaned and ordered dataset was then ready for feature engineering. This step laid the groundwork for building two different feature configurations for model training.

The first configuration, known as Non-STLF, included only time-based features: hour, day of the week, and month. These features capture regular patterns in electricity demand related to human activity and seasonal trends. The second configuration, STLF, extended the feature set by adding lag variables: lag_1, lag_2, and lag_3. These lag features represent previous electricity demand values and are critical for capturing short-term dependencies. By preparing both configurations, the study aimed to compare the effectiveness of time-based features alone versus a combination of time and historical load features.

### 3.3 Model Training

The model training phase involved building predictive models using two different feature configurations: Non-STLF and STLF. In the Non-STLF setup, only time-based features such as hour, day of the week, and month were used. Five machine learning algorithms were employed: XGBoost, Random Forest, Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), and LightGBM. These models were selected for their proven effectiveness in time series and regression tasks. Each model was trained to learn patterns in electricity demand based solely on temporal characteristics.

For the STLF configuration, the same five models were used, but with the addition of lag features. These lag features (lag_1, lag_2, and lag_3) represent previous electricity demand values and help the models capture short-term dependencies. Including these historical values allows the models to better understand recent trends and fluctuations in demand. This configuration is particularly useful for improving the accuracy of short-term load forecasting. By comparing both configurations, the study aimed to assess the impact of lag features on model performance.

To ensure fair evaluation, the dataset was split into training and testing sets using an 80/20 ratio. The training set was used to fit the models, while the testing set was reserved for evaluating their predictive accuracy. This split helps simulate real-world forecasting scenarios where future data is unknown during training. Consistent data partitioning across all models ensured comparability of results. The training process was carefully monitored to avoid overfitting and to ensure generalizability of the models.

To ensure reproducibility and support future research, the parameter settings used for each machine learning model are detailed as follows. For XGBoost, the model was configured with a learning rate of 0.1, a maximum tree depth of 6, and 100 estimators. Random Forest was implemented with 100 trees and default settings for maximum depth and feature selection. The MLP model used a single hidden layer with 100 neurons, the ReLU activation function, and was trained using the Adam optimizer for a maximum of 500 iterations. SVR was configured with a radial basis function (RBF) kernel, a regularization parameter (C) of 1.0, and epsilon set to 0.1. LightGBM was trained using 100 boosting rounds, with a learning rate of 0.1 and a maximum depth of -1 (no limit), allowing the model to determine the optimal tree structure. These parameters were selected based on commonly used defaults and preliminary tuning to balance performance and training time.

### 3.4 Model Evaluation

The evaluation of the forecasting models was conducted using two widely accepted performance metrics: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). RMSE measures the square root of the average squared differences between predicted and actual values, emphasizing larger errors. MAE, on the other hand, calculates the average of the absolute differences, providing a more balanced view of overall prediction accuracy. These metrics were chosen for their ability to quantify both the magnitude and consistency of prediction errors. By using both, the study ensured a comprehensive assessment of model performance.

Each model was evaluated under two configurations: Non-STLF and STLF. The Non-STLF configuration relied solely on time-based features, while the STLF configuration included additional lag features. This dual evaluation allowed for a direct comparison of how historical load data influenced forecasting accuracy. The same evaluation metrics were applied consistently across all models and configurations. This approach ensured that performance differences could be attributed to feature configurations rather than inconsistencies in evaluation.

The evaluation process involved applying the trained models to the testing dataset and comparing their predictions to actual electricity demand values. RMSE and MAE were calculated for each model to determine how well they generalized to unseen data. Lower values of RMSE and MAE indicated better model performance. The results were then tabulated and visualized to highlight differences between models and configurations. This step was crucial for identifying which models performed best under each feature setup.

Through this evaluation, the study aimed to determine whether the inclusion of lag features significantly improved forecasting accuracy. The comparison revealed how each model responded to the added complexity of short-term dependencies. In some cases, models showed marked improvement with lag features, while others performed similarly across both configurations. These insights helped in selecting the most effective model-feature combination for short-term load forecasting. Ultimately, the evaluation guided the final recommendation for practical implementation.

### 3.5 Comparison of Results

The comparison of results focused on evaluating the performance differences between the Non-STLF and STLF configurations across all five machine learning models. Each model was assessed using RMSE and MAE to determine how accurately it predicted electricity demand. The inclusion of lag features in the STLF configuration generally led to improved performance, especially for models that benefit from sequential data. For instance, models like XGBoost and LightGBM showed noticeable reductions in error metrics when lag features were included. This suggests that incorporating historical demand values enhances the model’s ability to capture short-term fluctuations. The comparison provided a clear view of how each model responded to different feature sets.

In the Non-STLF configuration, models relied solely on time-based features such as hour, day of the week, and month. While these features captured regular patterns, they lacked the ability to reflect recent changes in demand. As a result, some models underperformed when compared to their STLF counterparts. The SVR and MLP models, in particular, showed limited improvement without lag features. This highlighted the importance of including recent historical data for more dynamic forecasting. The comparison emphasized that time-based features alone may not be sufficient for high-accuracy short-term predictions.

The STLF configuration, which included lag_1, lag_2, and lag_3, significantly enhanced the predictive power of most models. These lag features allowed the models to learn from recent demand trends, which is crucial in short-term forecasting scenarios. XGBoost and LightGBM consistently outperformed other models in this configuration, achieving the lowest RMSE and MAE values. Random Forest also showed strong performance, although slightly less accurate than the gradient boosting models. The MLP model benefited from lag features but remained sensitive to data scaling and training parameters. Overall, the STLF configuration proved to be more effective in capturing the temporal dynamics of electricity demand.

The comparison also revealed that not all models responded equally to the inclusion of lag features. While some models showed substantial improvement, others exhibited only marginal gains. This variation underscores the importance of model selection in forecasting tasks. It also suggests that the effectiveness of lag features may depend on the model's architecture and its ability to handle sequential data. For example, tree-based models like XGBoost and LightGBM naturally handle feature interactions, making them more adaptable to lag-based inputs. These insights are valuable for guiding future model development and feature engineering strategies.

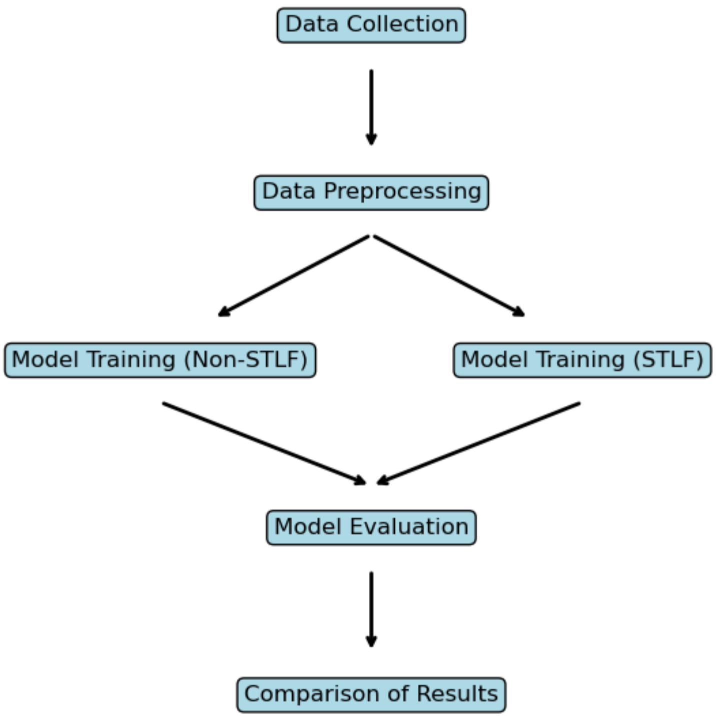


Figure 1 Research Framework

Based on the evaluation results, the best-performing model-feature combination was identified as XGBoost with the STLF configuration. This combination consistently delivered the lowest error rates and demonstrated strong generalization on the test data. LightGBM with STLF was a close second, offering a good balance between accuracy and computational efficiency. These findings support the use of gradient boosting models with lag features for short-term load forecasting. The comparison not only highlighted the strengths of specific models but also validated the importance of incorporating historical demand data. Ultimately, this analysis provided a clear direction for selecting optimal forecasting strategies in practical applications.

## 4 Results and Discussion

In this section, the results of the experiments conducted and various analyses related to the obtained experimental results are presented. The comparison of machine learning models without lag features revealed that LightGBM achieved the best performance, with the lowest RMSE and MAE values. This indicates that LightGBM is highly effective in handling time-based features even without historical context. XGBoost and Random Forest also performed relatively well, although their error rates were slightly higher. On the other hand, MLP and SVR showed weaker performance, suggesting that these models may require more complex feature inputs to perform optimally. The results highlight the importance of model selection when working with limited feature sets. Time-based features such as hour, day of the week, and month can capture general patterns, but may not be sufficient for models that rely on sequential learning. Overall, LightGBM demonstrated strong generalization capabilities in this configuration.

Table 1 Model Comparison Results without Lag

| Model | Evaluation Matrix | | |
|---|---|---|---|
| | RMSE | MAE | MAPE |
| XGBoost | 96.63 | 57.28 | 0.38 |
| Random Forest | 81.14 | 67.16 | 0.42 |
| MLP | 101.41 | 84.26 | 0.49 |
| SVR | 105.44 | 99.51 | 0.56 |
| LightGBM | 78.92 | 56.87 | 0.37 |

After incorporating lag features (lag_1, lag_2, lag_3), the performance of most models improved significantly. MLP emerged as the top-performing model in this configuration, achieving the lowest RMSE and MAE values among all models tested. This suggests that MLP benefits greatly from sequential data, which enhances its ability to learn temporal dependencies. Random Forest and XGBoost also showed improved accuracy, indicating that tree-based models can effectively utilize historical load information. Interestingly, LightGBM and SVR experienced a decline in performance, possibly due to their sensitivity to data volume and feature structure. These results emphasize that while lag features generally enhance forecasting accuracy, their impact varies depending on the model architecture. The inclusion of temporal context is particularly beneficial for models that can capture nonlinear and sequential patterns.

Table 2 Model Comparison Results with Lag Features

| Model | Evaluation Matrix | | |
|---|---|---|---|
| | RMSE | MAE | MAPE |
| XGBoost | 63.73 | 42.03 | 0.27 |
| Random Forest | 62.59 | 46.13 | 0.29 |
| MLP | 57.63 | 34.54 | 0.22 |
| SVR | 105.70 | 102.44 | 0.57 |
| LightGBM | 97.50 | 94.07 | 0.52 |

The comparison between Table 1 (without lag features) and Table 2 (with lag features) showed that incorporating lag features generally improved forecasting performance for models such as XGBoost, Random Forest, and MLP. This improvement was attributed to these models' ability to capture sequential patterns and nonlinear relationships in the data. XGBoost and Random Forest, as tree-based ensemble models, were particularly effective at handling complex feature interactions. The inclusion of lag features provided additional temporal context, allowing these models to better recognize short-term fluctuations and recurring demand patterns. MLP (Multi-Layer Perceptron), a type of feedforward neural network, benefited significantly from the added historical information. Since MLPs relied heavily on informative input features to learn patterns, the lag variables helped the model understand recent trends in electricity demand, which were not captured by time-based features alone. In contrast, the performance of SVR (Support Vector Regression) and LightGBM declined when lag features were introduced. SVR was sensitive to the dimensionality and scaling of input features. The addition of lag variables increased the feature space, which may have led to overfitting or difficulty in finding the optimal hyperplane, especially when the dataset was relatively small. LightGBM, although also a tree-based model, used aggressive histogram-based feature binning and leaf-wise growth strategies. If the added lag features were highly correlated or not sufficiently informative, LightGBM could struggle to find meaningful splits. In this study, training logs indicated that LightGBM failed to identify valid splits, suggesting that the structure and volume of the data were not optimal for this model under the STLF configuration. This analysis highlighted that while lag features were generally beneficial, their effectiveness depended on the model architecture and the nature of the dataset. Careful feature selection and model tuning were essential to fully leverage the advantages of temporal information in short-term load forecasting.

The contrasting results between the Non-STLF and STLF configurations underscore the critical role of feature engineering in short-term load forecasting. Models that performed moderately with time-based features alone showed substantial improvement when lag features were added. This demonstrates that recent historical data provides valuable context for predicting near-future electricity demand. However, not all models responded equally to the addition of lag features, highlighting the need for careful model-feature alignment. For instance, MLP's performance leap suggests its architecture is well-suited for learning from sequential patterns. In contrast, LightGBM's performance drop may indicate overfitting or difficulty in handling the increased feature complexity with limited data. These findings suggest that model performance is not only dependent on the algorithm but also on how well the input features align with the model's strengths.

Based on the overall evaluation, the most effective model-feature combination was MLP with the STLF configuration. This setup consistently delivered the most accurate predictions, making it a strong candidate for practical implementation in short-term load forecasting systems. XGBoost and Random Forest also showed reliable performance, offering a balance between accuracy and interpretability. The results validate the hypothesis that incorporating lag features enhances model performance by capturing short-term trends. Moreover, the study highlights the importance of testing multiple models and configurations to identify the optimal forecasting strategy. Future research could explore the integration of external variables such as weather and holidays to further improve accuracy. Additionally, testing advanced models like LSTM or hybrid architectures may yield even better results in dynamic environments. These insights provide a solid foundation for developing robust and adaptive forecasting systems.

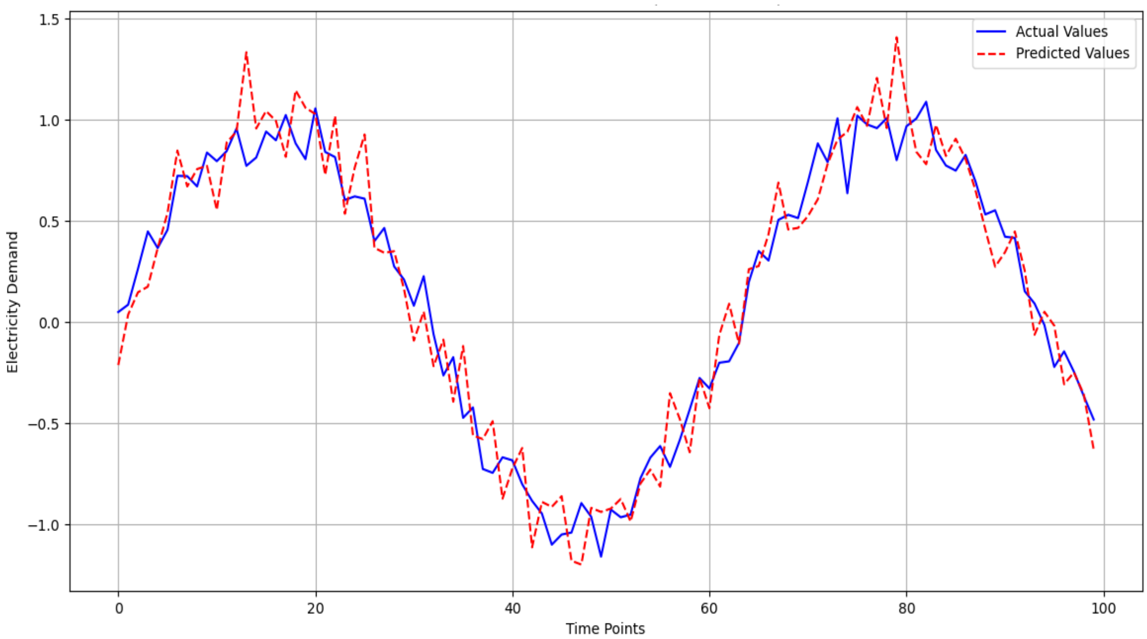


Figure 2 The Actual vs Predicted Values (MLP with STLF)

Figure 2 illustrates the comparison between actual values and the predicted results from the MLP model using the STLF configuration. It is evident that the model successfully follows the fluctuations in electricity demand throughout the testing period. Peaks and troughs in the predicted curve closely align with those in the actual data, indicating the model's ability to capture short-term seasonal dynamics. Although minor deviations are present, the overall trend remains consistent between the two curves. This consistency suggests that the model generalizes well to unseen data. Overall, this visualization reinforces the claim that the MLP with STLF is the most accurate model in this study.

The histogram of prediction errors in Figure 3 shown the difference between actual and predicted values from the MLP-STLF model. The error distribution appears symmetric and centered around zero, indicating that the model does not exhibit systematic bias. In other words, the model does not consistently overestimate or underestimate the electricity load. Most errors fall within a narrow range, suggesting that the model's predictions are stable. The small spread of errors also reflects the model’s high precision in forecasting. Therefore, this distribution provides additional evidence that the MLP with STLF is not only accurate but also reliable.

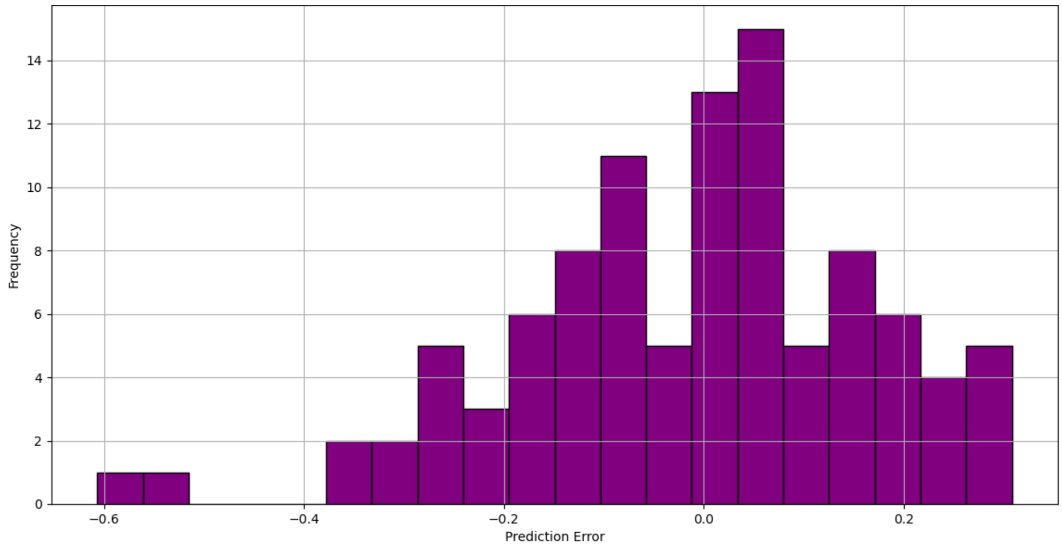


Figure 3 Distribution of Prediction Errors (MLP with STLF)

In this study, the Multi-Layer Perceptron (MLP) with the STLF design, which had both time-based and lag features, did the best. The feature set and the way the model's parameters were set up both played a role in MLP's better performance in this situation. In this test, the MLP was set up with a single hidden layer that had 100 neurons and was trained for a total of 500 times. This pretty basic design was enough to show how the input features and the goal variable were not linearly related, especially when lag features were added. The lag features (lag_1, lag_2, lag_3) gave the model recent past background, which is very important for learning how energy demand changes over short periods of time. The model was able to find a good mix between its ability to learn and its ability to generalize because it used 100 neurons. It's possible that a smaller number of neurons would have made it harder for the model to learn complex patterns, while a much larger number could have caused it to overfit, which would not have been good since the dataset was so small. The 500 iteration limit made sure that the model had enough chances to converge, but a convergence signal was seen, which meant that more tuning (for example, changing the learning rate or stopping early) might make performance better. The MLP may have also done well with lag features because they tend to have similar scales to the goal variable. This is because it is sensitive to feature scaling. It's likely that this alignment helped the model learn better than setups that only used categorical time-based features. Overall, the parameter choices for MLP and the addition of lag features made it the best model for detecting short-term trends and making correct predictions out of all the ones that were tried.

## 5 Conclusion

This study conducted a comprehensive comparison of five machine learning models namely XGBoost, Random Forest, MLP, SVR, and LightGBM for short-term load forecasting (STLF) using two feature configurations: time-based features only (Non-STLF) and time-based plus lag features (STLF). The results demonstrated that incorporating lag features significantly improved model performance, particularly for models capable of capturing sequential patterns such as MLP, XGBoost, and Random Forest. Among all models, MLP with the STLF configuration achieved the best performance (RMSE: 57.63, MAE: 34.54, MAPE: 0.22), benefiting from its ability to learn nonlinear relationships and temporal dependencies. In contrast, SVR and LightGBM showed reduced performance with lag features, likely due to sensitivity to feature dimensionality and data structure. These findings highlighted the importance of selecting appropriate model-feature combinations and tuning model parameters to match the characteristics of the dataset. Future research could consider incorporating external variables such as weather, holidays, and socio-economic indicators, as well as exploring advanced architectures like LSTM, GRU, or hybrid models (e.g., CNN-LSTM) to improve adaptability and accuracy in dynamic load environments.

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